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Research on Dissolved Oxygen Control during Biological Sewage Treatment

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This paper has put forward a dissolved oxygen control method based on MPC. The method has utilized the aforementioned simulation software package for generating large amounts of data, acquired state space model of the DO value process through identification, and simultaneously designed an MPC controller whose parameters are gradually determined by the common trial-and-error method. In simulation, it firstly carries out contrast verification of controller performance under different controller parameters so as to determine better controller parameters and lay the foundation for DO value process control. Secondly, it conducts control performance research on the activated sludge process by parameters-defined MPC controller and a comparison between built-in PI control strategies based on IWA and COST Benchmark. Results show that this controller performs better, and the DO value becomes more stable and less undulant. The proposed method has two advantages: first, fewer DO activities may make the activated sludge process more stable and reliable and thus lead to better processing effects; second, poorer DO fluctuations would exert little load for heating blowing machines, which is conducive to its energy-saving operation and consequently will provide conditions for low-cost operation of the whole activated sludge process.

1. Introduction

Biochemical oxygen demand refers to the amount of dissolved oxygen consumed during organism decomposition of microorganisms in surface water, and the standard unit of measurement is mg/L. Generally speaking, the process of microorganism decomposition can be divided into two phases: the first phase is the process during which the organism is converted to carbon dioxide, ammonia and water; the second phase is the so-called nitrifying process during which ammonia is further converted to nitrite and nitrate in the forms of nitrosobacteria and nitrifying bacteria (Ternes, 1998). BOD commonly refers to oxygen consumption of a biochemical reaction in the first phase. BOD reflects the total amount of organisms which can be decomposed by microorganisms in water. Water with less than 1mg/L BOD is considered clean water, and BOD of more than 3-4mg/L indicates that the water has been polluted by organisms. However, due to the long measuring time needed for BOD and restricted organism activities in sewage with great toxicity, it is difficult to obtain an accurate measurement (Ternes et al., 1999; Ternes et al., 1999).

Chemical oxygen demand refers to the amount of oxidant used by oxidizable matters in water during chemical oxidation under specified conditions, and the standard unit of measurement is mg/L. During COD measurement, organisms are oxidized into carbon dioxide and water (Castiglioni et al., 2006). The level of difficulty of chemical oxidation reaction varies among different organisms in water, and thus the chemical oxygen demand can only indicate the total oxygen demand of utilizable matters in water under specific conditions (Vieno et al., 2007; Tauxe-Wuersch et al., 2005; Perrone and Amelio, 2006).

Comparing COD with BOD, measurement of COD is not restricted by water quality and has a relatively short measuring time. But COD cannot distinguish an organism that can be biologically oxidized from that which is difficult to be biologically oxidized, and it also cannot represent the amount of organisms that can be oxidized by microorganism. Furthermore, chemical oxidants cannot oxidize all organic matter, and will oxidize some inorganic matter (Lagana et al., 2004; Zorita et al., 2009). Therefore, BOD is appropriately adopted as the indicator of the degree of organism pollution; when BOD measurement is restricted by water quality, COD can be substituted.

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Dissolved oxygen plays an important role during the biological sewage treatment through activated sludge (Stasinakis et al., 2008). The stability of dissolved oxygen concentration determines the degree of all biochemical reactions in sewage. Without enough DO, aerobic microorganisms can neither survive nor bring oxygenolysis into play. However, with extremely high DO concentration, unconsumed DO will reflow to hypoxia parts along with reflux inside the activated sludge, and the rate of organism oxidation will increase. This leads to a decreasing denitrifying nitrogen-removal process due to the absence of or insufficient carbon sources (Wagner and Loy, 2002). Moreover, if DO concentration in the aerobic zone is too low or close to 0, facultative bacteria will be transferred to anaerobic respiration, and most aerobic bacterium will basically stop breathing, while some aerobic bacterium (mostly filamentous bacterium) may grow well and thus their dominant positions in the system will cause sludge expansion. Thus, a suitable DO value must be maintained. In other words, during biological sewage treatment, DO value control has become necessary for realizing quality standardization of sewage treatment (Postigo et al., 2010).

Under current actual conditions, DO is still in semi-automatic control or even manual control during most sewage treatment processes and has commonly adopted the traditional PID control algorithm with unsatisfactory control effects (Yu et al., 2009; Metcalfe et al., 2003). As a result, product quality cannot be guaranteed, and the environment has suffered serious pollution while at the same time raw materials are being severely wasted. Although control research on such a process globally has achieved some results, actual production and application requirements still cannot be met. Therefore, how to apply modern intelligent control technology and means to achieve a stable and accurate control of DO value is still an exceedingly challenging task.

As dissolved oxygen control of sewage treatment is a control object with complex characteristics including nonlinearity, high time lag and strong interference, it is not easy to achieve satisfactory results (Svenson et al., 2003). If we adopt intelligent control technology and a high-level automatic control system, the effect and efficiency of sewage treatment will be greatly improved, resulting in tremendous social and economic benefits will be. Consequently, research conclusions of this paper are of high value in terms of both theory and application (Metcalfe et al., 2003; Solé et al., 2000).

2. Materials and methods

2.1 Model Predictive Control

The method of model predictive control (MPC) is a new computer control algorithm comprising three elements including model prediction, rolling optimization and feedback correction. Its successful application in some complex industrial processes such as oil refining, the chemical industry and electric power has attracted much attention to MPC. At present, corresponding theoretical research on MPC is a point of widespread interest in the control theory field and has become one of the most representative advanced control strategies in the field of industrial process control.

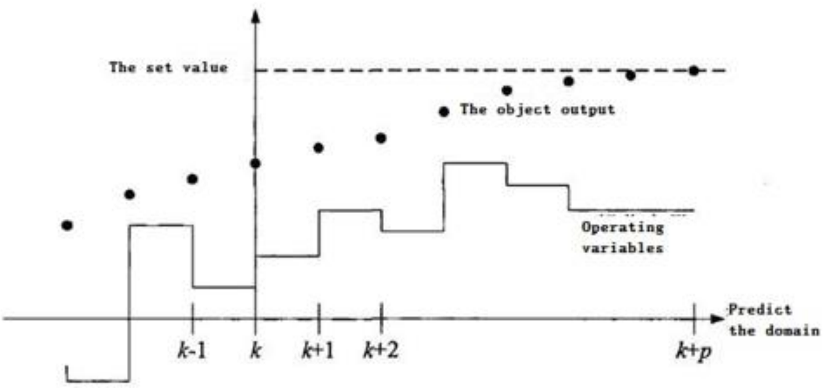


Figure 1: MPC Control process

In 1978, the model of predictive heuristic control proposed by Richalet et al. has long been applied to predictive control algorithm for the actual industrial process, and its core idea is as follows. On the basis of control strategy of online optimization, the current state of the system at each sampling time is taken as the initial condition. The dynamic model of the process is utilized, and the system response is predicted within a limited time domain. An open-loop optimization problem is solved and a control sequence is obtained according to the future performance indicator of this model's optimization object. Then, the first controlled quantity of this control sequence is applied to the controlled object. Because on-line rolling optimization is adopted in the predictive control algorithm and the difference between the actual system output and the predictive model output is used for feedback and correction during optimization, the predictive model output can to a certain degree overcome the predictive model's influences of deviation and some indeterminate interference. Hence, MPC control strategy will be selected as the process control method of DO value in this study, and the effectiveness of the control strategy will be verified under the benchmark.

Figure 1 shows the control process of MPC. In this study, the set value is just that of the DO concentration in No.5 biochemical reaction tank (aeration tank). It is generally thought that the DO concentration should be maintained at around 2mg/L, and the object output is the DO concentration value in the tank as detected by sensors. In this control simulation research, the DO concentration can be acquired through an ideal soft sensor model which is adopted to read the corresponding data in the process object. The sensor at the time is set as ideal sensor; that is, it boasts characteristics such as no time delay and measurement noise interference, and the operating variable is the mass transfer coefficient of dissolved oxygen—K_La.

Figure 2 shows the control principle diagram of the DO process designed under MPC guidelines. Assuming that the temperature remains unchanged during processing, in order to maintain a constant DO value in the aeration tank, DO concentration appeared as the same measurement as the ideal sensor placed in the aeration tank, and a comparison was made between MPC controller and DO set value. The value of operating variable is adjusted by operating variables and used to regulate DO concentration in the tank. Repetition of procedures including prediction, optimization and feedback correction in such a process will maintain the DO concentration at a certain range of set values and finally achieve the goal of DO process control.

For the assumed control increment of m steps (current or future), $\Delta u(k)$, $\Delta u(k+1),\cdots$, $\Delta u(k+m-1)$. So the predictive output of future p steps is $y(k+1|k)$, $y(k+2|k)$,……, $y(k+p|k)$. However, current or control increment of future m step (m<p) is then obtained by minimum value of the following secondary goals through calculation:

$$\min_{\Delta u(k),\Delta u(k+1),\cdots,\Delta u(k+m-1)} \sum_{l=1}^{p} \left\| \Gamma_l^y \left[y(k+1|p) - r(k+l) \right] \right\|^2 + \sum_{i=1}^{m} \left\| \Gamma_l^y \left[\Delta u(k+l-1) \right] \right\|^2 \tag{1}$$

It is also subject to the constraints of the following inequalities:

$$\begin{aligned} & y \le y(k+j) \le \bar{y},\ j = 1,\cdots,p \\ & u \le u(k+j) \le \bar{u},\ j = 0,\cdots,m-1 \\ & \Delta u \le \Delta u(k+j) \le \overline{\Delta u},\ j = 0,\cdots,m-1 \end{aligned} \tag{2}$$

In formula (1), Γ_l^y and Γ_l^u are weight matrices used for penalizing specific variables (y or u) in predictive time domain as the future set value vector. Although m steps control increment $\Delta u(k)$, $\Delta u(k+1),\cdots$, $\Delta u(k+m-1)$, will be calculated in rolling optimization, only the first control increment will be implemented. Thus, when the next sampling interval comes, the control domain will move a step further in rolling optimization. Along with new output values collected from the process object and repetition of aforementioned calculation process, the first new control increment is implemented again and thus the optimization control of the process object can be achieved through such repetition. Predictive outputs of object $y(k+1|k)$, $y(k+2|k)$,……, $y(k+p|k)$ are dependent on the actual output of present objects. Assuming that $y(k)$ at this time contains influences of immeasurable perturbations and measurable noises, then as a result, in the simulation research, measurable noises have been manually added into the object output so as to test the effectiveness and dynamic response capacity of the control strategy. Except for operating variable K_La, input variables of the aeration tank are all assumed as immeasurable perturbations of the system.

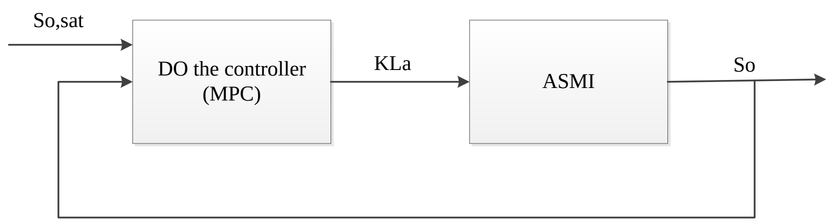


Figure 2: DO value of the process control

2.2 Type font and type size

By the steady-state simulation carried out through the aforementioned BSM1 platform, steady-state simulation data can be acquired in terms of various degrees of aeration and thus the continuous time state space model can be established in the following form:

$$\frac{dx}{dt} = Ax + Bu \qquad (3)$$
$$y = Cx + Du$$

In the formula, x is the state vector, while u and y are respectively input and output vectors; A, B, C and D are respectively state space coefficient matrix. Figure 3 is the step response curve of the model identification by the system under various degrees of aeration. The figure has established step response curves directing at 3 dissolved oxygen concentration grades in the aeration tank respectively at 2mg/L, 1.4mg/L and 0.9mg/L. It is generally recognized that DO concentration should maintain at around 2mg/L, and therefore from the step response (blue dotted lines in Figure 3) of its identification model, it can be obtained that:

2.3 Type font and type size

Simulation research of controller responsiveness is processed through continuous state space coefficient matrix with the above method, and controller parameters are set as follows: sampling time Δt=2.5×10^{-4}*day* =20*S*, Γ^u=0.01, *m*=1, *p*=10. The results are shown as green dashed lines in Figure 4a. In order to verify the control performance of the controller, DO set value was changed from 2mg/L to 2.3mg/L when t=0.03day during simulation, and the DO concentration in water entry was reduced by 1mg/L when t=0.07day, as shown in blue solid lines in Figure 4a. In both cases, the controller can make a quick control response for DO concentration and thus achieve better results.
Meanwhile, in order to verify the control performance of the controller under different parameter settings, controller parameters are adjusted as follows: in Figure 4A, the red dotted line is the controller response curve obtained by decreasing predicted domain (p=6), and the bluish green dashed line is the controller response curve obtained by enlarging the weight value of variable penalty(Γ^u=0.1).

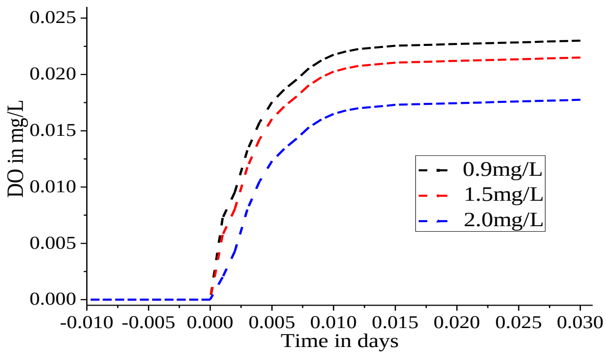
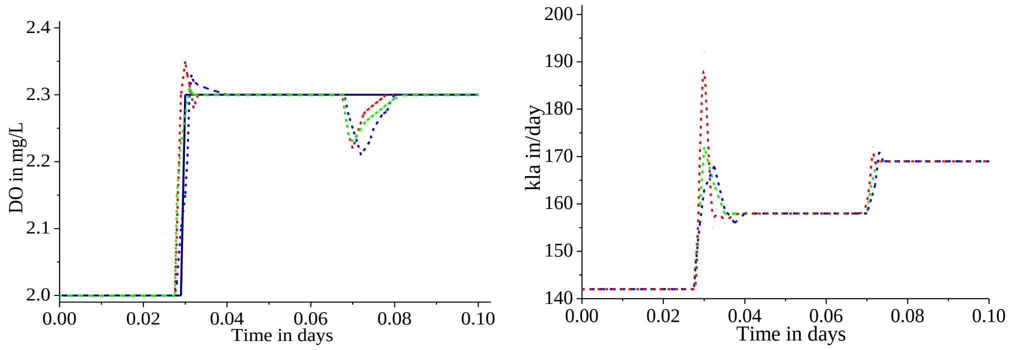


Figure 3: Identification model under various degrees of aeration step response curve



(a) (b)

Figure 4: Controller response performance simulation under various control parameters

It can be seen from the comparison results in Figure 4a that narrowing predictive domain can shorten controller response time, although an overshoot may increase larger; while enlarged input of variable penalty will enhance response time and overshoot enhance. Output changes of operating variable K and a are shown in Figure 4b: there is evident variation at time points of t=0.03day or t=0.07day (in all aforementioned cases, line color in the figure corresponds to that in figure 4a), and a conclusion can be drawn in accordance with that in Figure 4a.
In Figures 4 and 5, it is certain that performance of the controller is closely related to its parameters, such as sampling time, predictive step length, input weight value, etc. Therefore in actual use of the MPC controller, a trial-and-error method is usually adopted to repeatedly debug parameters of the controller and lastly determine its parameter configuration for an optimal balance under basic performances including response time and overshoot, which can help control process be more stable and reliable.

3. Results and discussion

Figure 6 shows control performance simulation comparison of the strategy in this paper (red solid line) and the PI control strategy (green dashed line). As can be seen from the figure, the strategy in this paper is superior to the PI control strategy in control accuracy, deviation, and response time.

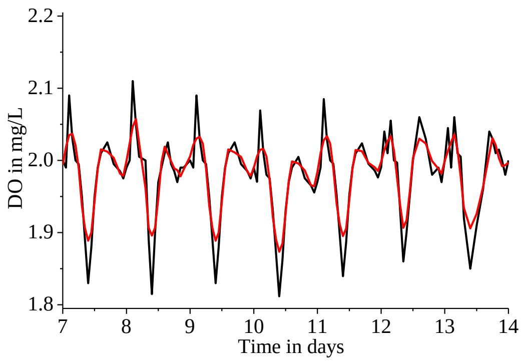


Figure 5: Performance of the controller

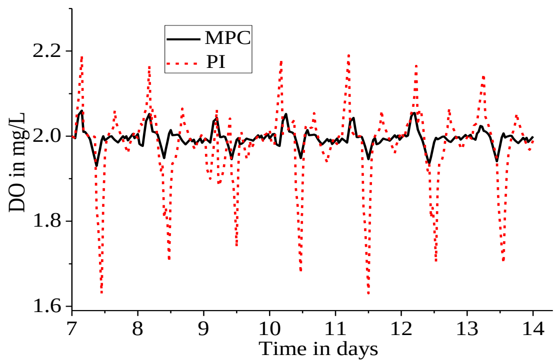


Figure 6: Comparison of control simulation

4. Conclusion

This paper has put forward a dissolved oxygen control method based on MPC. The method utilized the aforementioned simulation software package for generating large amounts of data, acquired the state space model of DO value process through identification, and designed the MPC controller whose parameters are gradually determined by the common trial-and-error method. In simulation, it firstly conducted contrast verification of controller performance under different controller parameters settings so as to determine better controller parameters and lay the foundation for DO value process control. Secondly, it conducted control performance research on activated sludge process by the parameters-defined MPC controller and made a comparison between built-in PI control strategies based on IWA and COST Benchmark. Results show that this controller performs better, and the DO value becomes more stable and less undulant. The proposed method has two advantages: first, smaller DO activities may make the activated sludge process more stable and reliable and thus lead to better processing effects; second, poorer DO fluctuations would exert little load for heating blowing machines, which is conducive to its energy-saving operation and consequently will provide conditions for low-cost operation of the whole activated sludge process.

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Research on separating characteristics and the application of water supply of ash materials from biomass power plant.

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